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RESEARCH ARTICLE

Multi-Band and Multi-Network Cooperative Transmission Algorithm for Wireless Resource Optimization

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ABSTRACT The emergence of various high bandwidth services has led to increasing demands for data transmission speed. Nowadays, a single network can no longer meet the diverse business needs of customers at any time. Therefore, utilizing wireless networks to achieve multi-path parallel transmission is an important approach. A multi-path parallel transmission control method is proposed to avoid the congestion and chaos of the receiver, so as to improve the transmission efficiency. Reinforcement learning is used to intelligently select the size and redundancy of code packets to overcome data packets chaos. Meanwhile, considering that network transmission services may become paralyzed after congestion occurs, this study also proposes a Q-learning-based congestion control algorithm. These results indicate that the network resource optimization algorithm proposed by this research can dynamically adjust the length of packets and redundant packets within packets based on network conditions, making it suitable for various network situations. The adaptive linear network coding method is usedtoget a larger buffer space faster, which takes 8 seconds. The congestion control algorithm proposed by the research can maintain a bandwidth utilization rate of nearly 99% while maintaining a high transmission rate. This shows that the proposed linear network coding transmission method can effectively improve the problem of packet disorder in multi-user information fusion and improve the efficiency of multi-user information fusion. A new network congestion control method proposed by the research can ensure the rapid recovery of the network after congestion while ensuring the transmission quality of the network.

INDEX TERMS Wireless network, data, congestion control, parallel transmission.

I. INTRODUCTION

When the internet is deeply integrated with various vertical industries, it will occupy an important position in many application scenarios, such as intelligent factories, autonomous driving, monitoring, etc., in future internet business. In addition, in the future, the service target of the Internet will not only be mobile phone terminals. In the new smart city and the future industrialinternet, there will be thousands of new devices, such as smart wearable devices, smart home terminals,autonomous robots, etc. Major industrial enterprises have increasingly high requirements for their business applications and have put forward higher requirements [1]. So, a more elastic and universal network is an inevitable trend for future development. In today's rapidly developing world, a single wireless communication system is no longer able to adapt to the complex and ever-changing business needs of the future. In future mobile communication systems, there will still be various wireless access technologies, forming a mobile communication system. The collaboration and integration of various communication technologies enable each system and network to leverage their respective advantages, thereby achieving diversified requirements for the network [2]. However, with the continuous increase of network traffic, the spectrum available for mobile phones is becoming less and less. Therefore, it is urgent to utilize multi-band collaborative communication to ensure the safety of users. The unlicensed band network represented

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by Wireless Local Area Network (WLAN) can effectively improve the spectrum utilization of mobile communication systems, thereby reducing the load on mobile communication systems. It can be extended to the millimeter wave band, and it can improve data transmission speed, reduce spectral pressure, and expand network capacity [3]. For future large-scale and high-density Internet of Things (IoT)services, relying solely on ground-based mobile networks cannot effectively solve this problem. Therefore, it is necessary to use un-manned aerial vehicles and other aerial communication carriers to carry out collaborative transmission with the ground, expand the coverage of the network, and meet the network service requirements of multiple coverage, large-scale, and intelligent inter-connection [4]. Collaboration and integration are the direction of future network technology development. In this context, due to the heterogeneity of networks and the diversity of services, existing wireless communication management technologies are no longer able to meet the requirements of seam-less switching, location management, and collaboration of wireless communication by terminals. This poses new requirements for the collaboration and integration of wireless communication systems [5]. In order to meet the diverse and personalized requirements of network services, it is necessary to effectively manage and optimize resources in multiple fields, in order to achieve complementarity, integration, and collaboration of multiple network services. In order to solve the problem of out of order of data packets, Network Coding (NC) is used to break the strong constraint between the serial number of data packets and the delivery order. Based on reinforcement learning, through the continuous interaction between agents and the environment, the optimal NC strategy is learned to improve the system throughput. NC is a technique that allows intermediate nodes to encode and transmit data, while reinforcement learning is a machine learning technique that learns the best behavioral strategies through interaction between agents and the environment. In addition, the study also uses reinforcement learning methods to reduce or avoid network congestion events, in order to reduce network latency.

The innovation of this study lies in proposing a multi-band,multi-network transmission control algorithm based on adaptive NC. On the basis of analyzing the problem of multi-path transmission, this algorithm introduces a reinforcement learning method, namely, Asynchronous Advantage Actor-Critic (A3C). And through the adaptive NC, the size of the encoding group and redundancy size based on the current network conditions are selected intelligently, thereby solving the data packet disorder.

The academic contribution lies in the fact that the proposed network transmission control algorithm helps to improve throughput performance, enabling the aggregated throughput to reach the sum of the throughput of multiple sub-flows, and promoting load balancing, enabling the congestion control of multi-path transmission systems to have the ability to balance the transmission load of multi-bands.

This study mainly includes the following four parts. Firstly, the literature review on wireless resource optimization and network cooperative transmission is presented. Secondly, it is the construction of a model for multi-path and multi-frequency band transmission in wireless networks and network congestion optimization. The following is an analysis of the performance results of the proposed model, mainly introducing the required environment for the experiment, evaluation indicators, and their results. Finally, there is a summary of the content after the experiment.

Table 1 is a comparison table of the full names and abbreviations of the relevant algorithm technologies used in the article.

TABLE 1. Comparison table of full names and abbreviations.

Full name	Abbreviation
Wireless Local Area Networks	WLAN
Network Coding	NC
Intelligent Reflection Surface	IRS
Algorithm for Queue Management	AQM
Active Network Coding	ANC
Asynchronous Advantage Actor-Critic	A3C
Orthogonal Frequency Division Multiple Access	OFDMA
Backpressure Bottleneck Routing	BBR
A modified version of the Reno algorithm for TCP	NewReno
A cubic congestion control algorithm for TCP	CUBIC
A common congestion control algorithm for TCP	TCP Reno
A compound TCP congestion control algorithm	Compound
A TCP congestion control algorithm based on cubic function	TCP Cubic

II. RELATED WORKS

Many scholars have conducted extensive research on wireless resource optimization. Wang C and other scholars proposed a storage resource management algorithm based on distributed deep reinforcement learning to schedule sufficient storage resources to centrally accommodate information uploaded by edge servers. In each edge physical domain, the network attributes represented by storage resources were extracted for the agent to construct a training environment and achieve distributed training. These results confirm that compared with other algorithms, the resource allocation benefits and user request acceptance rate of this algorithm have increased by more than 8% [6]. Luo Wet al. aimed to improve the minimum data collection rate of unmanned aerial vehicles in all IoT devices, so they designed an efficient iterative algorithm using the successive convex approximation method. These results confirm that the algorithm performs better than the simplified line of sight model algorithm and the two-dimensional trajectory optimization algorithm under different conditions [7]. Alsharoa et al. proposed a low complexity method based on frequency partitioning technology to solve correlation and power allocation. In the long-term stage, the position of HAPs was optimized by proposing effective algorithms based on recursive contraction and rearrangement processes [8]. Yang Get al. studied a drone assisted back-scatter communication network, which consisted of multiple ground base stations and carrier transmitters, as well as a drone. These simulation results confirm that the proposed flight time communication scheme achieves significant EE gain. They also gained useful insights on optimal trajectory design and resource allocation [9]. Xiao Het al. used Lagrange duality problem and sub-gradient projection method to iteratively approximate the optimal value for resource allocation problem. For local model accuracy issues, an adaptive harmony algorithm was proposed for heuristic search. These simulation results confirm that the proposed algorithm has good convergence and effectiveness, achieving a compromise between cost and fairness [10]. Khalid R et al. provided an overview of autonomous air networks with wireless power transmission. They discussed resource optimization and challenges faced by autonomous air networks with wireless power transmission. Subsequently, they provided a case study to maximize the computing efficiency of wireless power transmission [11]. Yang Zet al. considered a mobile edge computing platform supported by UAVs, which served multiple mobile ground users who moved randomly and arrived with tasks. These simulation results confirm that the proposed joint optimization method achieves better performance than the two-stage method at the cost of higher computational complexity [12]. Khan L Uet al. introduced the main design aspects of implementing joint learning at network edges. The Stackelberg game was used to model incentive-based interactions between global servers and devices participating in joint learning, to motivate devices to participate in the joint learning process [13].

In terms of network cooperative transmission, Xu Set al. proposed a satellite ground integrated network security cooperative transmission strategy supporting intelligent reflector. These simulation results confirm that the collaborative interference scheme can significantly reduce the SINR of the target at the eavesdropper, thereby obtaining a significant confidentiality gain [14]. Hiraguri T et al. proposed an uplink multi-user, multi-input,and multi-output cooperative re-transmission control scheme for reliable and efficient communication of autonomous drones. These results confirm that the proposed method achieves a direct transmission throughput of 1.5 times better than traditional schemes [15]. Xiong Wet al. proposed a user cache management and collaborative transmission mechanism based on edge community computing by establishing a community mechanism and taking advantage of the predictability of users' requests for popular content. By utilizing idle user device space through edge community computing to manage cache allocation for collaborative transmission, content delivery latency and load on micro base stations are reduced [16]. Yang K et al. proposed an energy-saving edge processing framework for performing deep learning reasoning tasks on edge computing nodes. Under the constraint of probabilistic quality of service, a joint inference task and downlink beam-forming problem were established with the goal of minimizing the sum of computation and transmission power consumption. This problem is represented by a set of sparse objective functions [17]. Jeong C et al. considered a cooperative wireless power transfer communication network to solve the problem that IoT devices are usually limited by energy. In addition, the time allocation of each stage is optimized based on the random gradient method. These numerical results confirm that the proposed beam-forming scheme and random time allocation can achieve near optimal performance [18]. Kim S H et al. proposed the cooperative transmission of wireless power transfer wireless networks assisted by back-scatter. To ensure the fairness between devices, they proposed the problem of maximizing the public throughput and gave a time allocation algorithm. The algorithm effectiveness was verified by comparing it with the optimal pairing based on heuristic search [19]. Kibinda N M et al. proposed a new user centric collaborative transmission-based handover scheme, namely the group cell handover scheme, aimed at reducing the handover rate in UDNs. These results confirm that compared with traditional single base station association and fixed area collaborative network topology switching methods, the proposed method reduces the switching rate by about 40% [20]. Guo Y Y et al. studied an energy-saving resource allocation strategy for amplifying and forwarding protocols used to forward data to destinations. Simulation results show that the proposed scheme has better performance in system energy efficiency than the traditional strategy andconvolutional neural network [21]. Li Z et al. studied wireless networks assisted by multiple Intelligent Reflective Surfaces (IRS). The goal is to maximize the weighted sum rate of all edge users in the cell by jointly optimizing the beamforming of the base station and the phase shift of the IRS. These numerical results confirm that IRS can significantly improve the gain [22].

In terms of network congestion control, Zhang T. et al. introduced the recent application of maximum likelihood method in the field of end-to-end congestion control, reviewed the relationship between congestion control and machine learning, and applied the maximum likelihood method to congestion control work, clarifying potential future research directions [23]. Grover A. et al. proposed a new rate aware congestion control mechanism that definedthree congestion levels based on data rate, throughput, overhead, and latency. The simulation results show that the overall improvement of this method compared to existing technologies follows an increase of over 15% in throughput parameters [24]. Khatari et al. conducted benchmark testing on active queue management methods for network congestion control using a grouping framework based on multi-criteria decision-making technology to help developers to choose the best AQM method [25].

To sum up, scholars have mainly conducted network transmission research on storage resources or UAV communication, and less attention has been paid to wireless networks. In view of this, this research will design an adaptive multi-network cooperative transmission algorithm to optimize wireless network resources. In terms of congestion control issues, scholars mainly design models based on hierarchical and decision-making optimization ideas, and rarely apply intelligent learning algorithms to adjust congestion windows. In view of this, this study will propose a new intelligent learning algorithm to improve the flexibility ofthe congestion control.

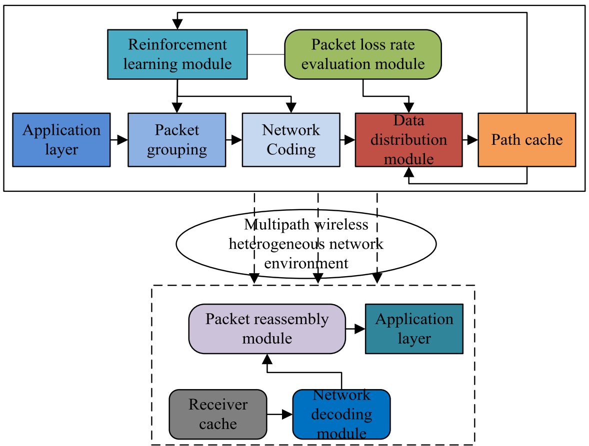


FIGURE 1. Architecture of wireless link cooperative transmission system based on adaptive coding.

III. CONSTRUCTION OF AN OPTIMAL MODEL FOR ADAPTIVE TRANSMISSION CONTROL OF MULTI-BAND AND MULTI-NETWORK WIRELESS LINKS

The concurrent transmission technology of multi-frequency band and multi-network inevitably generates phenomena such as queue head blocking and receiver disorder, seriously reducing transmission efficiency. To overcome the problems faced by multi-path transmission and maximize the advantages of convergence, this study proposes a multi-path concurrent transmission control algorithm based on adaptive NCto improve transmission rate. In addition,to solve the problem of network congestion caused by the increasing amount of massive information, a learning-based network congestion management algorithm is proposed.

A. MULTI-BAND AND MULTI-NETWORK DATA SCHEDULING MODEL BASED ON ANC

Unlike a single network, wireless networks expand the application scenarios of communication technology by increasing communication bandwidth and reducing latency due to their multiple network structures. Although the co-existence of multiple networks can help meet the needs of emerging mobile communication services, there are problems with dis-ordered reception and low transmission efficiency in data transmission. To address these issues, this study proposes a new end-to-end multi-path transmission model that introduces ANC to address encoding and decoding latency issues and packet reordering issues [26], [27]. The Active Network Coding (ANC) algorithm is a combination of NC and queue management, aimed at improving network throughput and performance. Figure 1 shows the architecture of wireless link co-operative transmission system based on adaptive coding.

From Figure 1, the transmission system consists of a sender, a multi-path wireless network, and a receiver. The sending end consists of a packet grouping unit, an NC unit, a data distribution unit, and a packet loss rate evaluation unit. Multi-path wireless networks contain several coexisting transmission links. The receiving end is composed of a network decoding unit and a data packet recombination unit. Equation (1) is the packet loss rate.

$$\begin{cases} pl_{t,i} = \alpha pl_{t-1,i} + (1-\alpha)\, pl_{t,i} \\ pl_{t,i} = 1 - \dfrac{Acked\_Packets}{Total\_Sent\_Packets} \end{cases} \tag{1}$$

In equation (1), α refers to the weighting factor. $pl_{t,i}$ refers to the weighted average packet loss rate of path i at time t. $Acked\_Packets$ is the confirmed data packet. $Total\_Sent\_Packets$ refers to the total number of packets sent. Therefore, the current packet loss rate value depends on the weighted average of historical values under various paths in the past. Accurate numerical calculation of packet loss rate will affect the judgment of reinforcement learning units and the rationality of data distribution. For reinforcement learning units, considering the interaction characteristics of the system, A3C algorithm is introduced to optimize it to accelerate the convergence speed of the model. A3C combines the method of policy gradient and value function to accelerate learning by parallelly processing the experience of multiple agents. It has been proven to perform excellently in many tasks. The asynchronous reinforcement learning algorithm is proposed based on Actor Critic. In the A3C algorithm, multiple threads interact with the environment separately, and each thread aggregates its learned knowledge to update the common neural network. At the same time, each thread obtains parameters from the public neural network at regular intervals and updates its own neural network parameters to better guide the subsequent interaction process with the environment. A3C adopts the Actor Critic architecture, where "Actor" is responsible for selecting actions and "Critic" is responsible for estimating state value functions. This method combines the advantages of strategy and value methods, enabling more efficient learning. Through the introduction of this idea, A3C overcomes the problem of strong correlation in experience playback during training, and also achieves asynchronous and concurrent learning. In the A3C algorithm, all threads share a common neural network, but they have their own copy of parameters. In this way, each thread can update its own parameters based on its experience, while the common neural network aggregates these updates. Figure 2 is a schematic diagram of A3C.

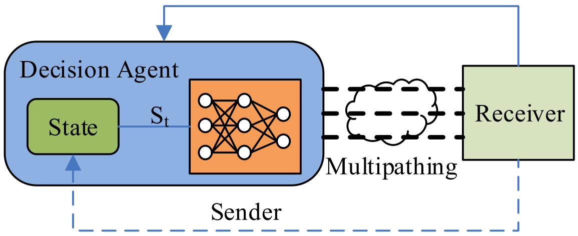


FIGURE 2. Diagram of A3C reinforcement learning.

From Figure 2, after inputting the network state, A3C algorithm selects and executes actions based on the network output value, and switches the network state through state transition probability [28]. The reward value is used to evaluate the effectiveness of executing actions. The reward value and the switched network state are used as feedback for decision task execution. After the intelligent agent executes an action, the system will transition to a new state based on the action and the current state. This new state will be input into the neural network for updating the network state. The network state is related to the decision output encoding result, and the system state in Figure 2 is defined by the parameters in the system state set of equation (2).

$$S_t = \{Bw_i, Buffer_t, (N, R), T, T_t, Pl_t\} \tag{2}$$

In equation (2), Bw_i refers to the average bandwidth of the i-th path at time t. $Buffer_t$ refers to the data buffer durationat time t. N and R represent encoding grouping and redundancy value size, respectively. T and T_t represent data transmission delay and download delay, respectively. Equation (3) is the probability of state transition.

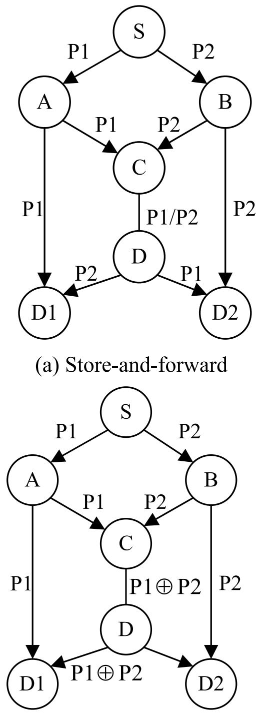
$$P^{a_t}_{S_t \to S_{t+1}} = P\left(S_{t+1} \,|a_t, S_t\right) \tag{3}$$

In equation (3), $P^{a_t}_{S_t \to S_{t+1}}$ refers to the probability of state transition occurring. S_t and S_{t+1} represent the environmental status at moments t and $t+1$. Therefore, the transferred state is only related to the current state and has Markov characteristics. Equation (4) is the reward function.

$$r_t = \log_2\left(\sum\nolimits_{i=1}^{I} Bw_i \times T_{t,i}\right) - \alpha \frac{2}{\left(1 + e^{(-rebuf)} - 1\right)} - \beta \log_2 (T) - \lambda B \tag{4}$$

In equation (4), r_t refers to the reward value. $\log_2\left(\sum_{i=1}^{I} Bw_i \times T_{t,i}\right)$ refers to the maximum throughput that the transmission can withstand. α and β represent the re-buffering penalty factor and delay penalty factor. λ refers toa buffer penalty factor. Figure 3 shows a comparison between store forward and NC mode.

NC unit's function is to use a linear combination method to reorganize the original data packets and generate updated data packets. From Figure 3, the traditional "store forward" mode only has routing function and does not perform computational processing on the route data packets. NC mode combines routing and encoding, and the intermediate nodes in the network have the ability to process data packets twice, thus increasing the efficiency of data transmission. Equation (5) is a packet encoding expression based on linear combination.



(a) Store-and-forward

(b) Linear network coding mode

FIGURE 3. Comparison between store and forward mode and linear network coding mode.

$$\sigma = c_1 P_1 \oplus c_2 P_2 \ldots \oplus c_k P_k \tag{5}$$

In equation (5), c_k refers to the linear combination coefficient. $\oplus$ stands for exclusive OR. σ refers to coded packets. The common linear coding method is pipeline NC, which is based on the lower triangular matrix to realize progressive coding. However, this method relies on the accuracy of network parameter values, and the coding speed is slow. In order to improve the existing encoding method, this study proposes an adaptive encoding strategy in Figure 4.

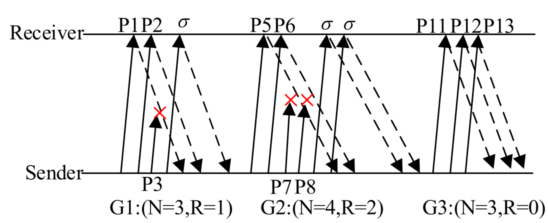


FIGURE 4. Schematic diagram of adaptive linear network coding.

In Figure 4, the adaptive NC scheme first obtains N and R values based on the reinforcement learning module. N values are the number of original packets and R values are the number of encoded redundant packets. TheNC module performs network coding on the received data packets, following a progressive coding strategy. The encoding matrix is agreed upon between the sender and receiver, and the encoding coefficients do not need to be carried in the data packet to reduce the size of the encoded data packet and save bandwidth resources. If the network state changes, it may cause a change in the number of original data packets N and the number of encoded redundant data packets R. In Wi-Fi communication, the signal frequency is usually in the frequency band of 2.4GHz or 5GHz. At the same time, different flag bits are set in the data packet to distinguish whether the data packet is encoded or redundant, and encoding and decoding coefficients are selected from the corresponding matrix based on different flags. Due to the fact that the size of the encoding group and the size of redundant data packets within the group are the optimal strategies learned by the reinforcement learning module based on network conditions, this encoding scheme is an adaptive network encoding scheme. The application of adaptive NC breaks the strong binding relationship between the packet sequence numbers and transmission sequences. As far as the receiver is concerned, it needs to accept enough coded packets to recover the original data packets without worrying about the sequence. Therefore, when the transmitter arranges data packets, it is expected to be able to send encoded data packets at an earlier time. Therefore, when constructing a data packet distribution unit based on path quality, it is necessary to calculate the quality of each route and select the best route each time in order to place the encoded data packet in its cache. Equation (6) is the mass of the i-th path.

$$Q_i = (effwnd_i - unAck_i) \times (1 - pl_i) \tag{6}$$

In equation (6), $effwnd_i$ refers to the maximum number of packets that can be sent on the i-th path. $unAck_i$ refers to the number of packets that have been sent to be determined for the i-th path. In view of the fact that the licensed bandwidth available in the current wireless communication system is very limited, Orthogonal Frequency-Division Multiple Access (OFDMA) technology is proposed for this study. In response to the bandwidth limitations and other issues in existing systems, OFDMA technology is introduced to reasonably configure various sub-carriers to improve system performance. Figure 5 is a schematic diagram of the common OFDMA technology.

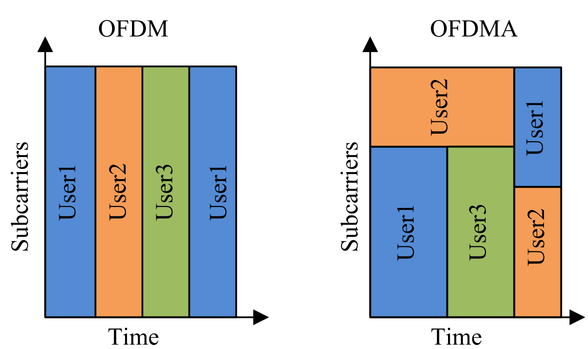


FIGURE 5. Schematic diagram of orthogonal frequency-division multiple access technology.

In Figure 5, OFDMA technology is a multi-access technology that divides the available spectrum into multiple sub-carriers in the frequency domain and allocates them to different users or data streams, thereby achieving simultaneous access and transmission for multiple users. OFDMA technology combines time and space division technologies, allowing users to use multiple sub-carriers within a certain time interval. At the network layer, OFDMA technology can support multiple users to access and transmit simultaneously, thereby improving network throughput and spectrum utilization. At the transmission layer, OFDMA technology can improve data transmission rate and reliability by optimizing sub-carrier allocation and modulation methods. After introducing OFDMA technology, the system performance can be optimized by configuring each sub-carrier reasonably, and achieving the segmentation of multiple sub-carriers within the same time interval.

B. DESIGN OF CONGESTION CONTROL ALGORITHM BASED ON Q-LEARNING

To maximize the available network resources, congestion control requires the detection of the maximum available bandwidth at all times, ensuring that the maximum available information does not exceed the maximum available bandwidth. Otherwise, it will cause information to be buffered, causing network congestion and increasing network transmission delay. Congestion control is related to the dynamic adjustment of congestion window size. To enhance the flexibility of window opening control, this study designs an adaptive congestion control algorithm based on model and data. Figure 6 shows the overall design content of this control algorithm.

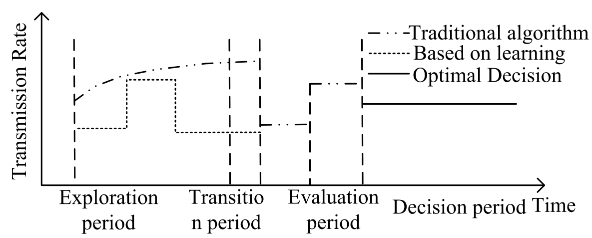


FIGURE 6. Schematic diagram of each stage of congestion control algorithm.

From Figure 6, each control cycle is divided into four stages, namely the exploration, transition, evaluation, and decision-making periods. In the exploratory stage, traditional data-based network congestion control methods are chosen, which are more advantageous in practical applications due to their strict network congestion control laws and are easy to implement. The main goal of this stage is to explore the network state and learn how to effectively control congestion based on this information. In the exploration phase, the backup algorithm for congestion control is the intelligent learning algorithm. When the difference between the width of the congestion window obtained by conventional methods and the width of the congestion window obtained through

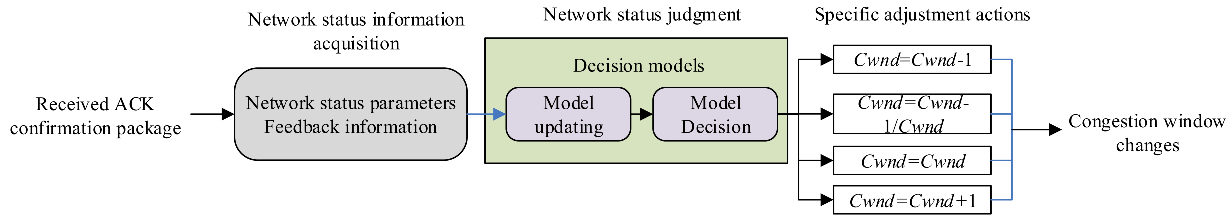


FIGURE 7. Congestion control-flow diagram based on Q-learning.

training exceeds a certain threshold, it will enter the transition stage. The purpose of the transition phase is to smoothly transition to the next phase, ensuring the stability of the network state and minimizing any network fluctuations that may occur due to algorithm transitions. During this period, it is still necessary to compare the differences between the two. If the duration of the differences between the two exceeds a specific time limit, the evaluation period will begin. During the evaluation phase, the evaluation time is divided into two sections. Existing learning-based methods are compared with traditional methods and their utility function values are solved. In the decision-making stage, the optimal control strategy from the previous cycle is used as a congestion control method, and its utility function value is solved. The decision during this period should be based on performance evaluation throughout the entire cycle, rather than just the results at a single point in time. Equation (7) is a mathematical expression for traditional congestion control mechanisms.

$$ACK : \Delta w = \frac{1}{w}; LOSS : \Delta w = -\frac{w}{2} \tag{7}$$

In equation (7), w refers to the width of the congestion window. If TCP sender receives a confirmed response signal, it will increase a congestion window. If TCP receives a LOSS message, it will determine that the network is congested. In order to reduce congestion, it is necessary to reduce the number of packets on the network. The existing packet loss-based network congestion control methods rely on specific control behaviors, and the time window control granularity for network congestion control is relatively large. In the event of packet loss, the sender will shorten the blocking time by half, greatly reducing data transmission speed and thus reducing the system's utilization rate. Therefore, selecting the appropriate window adjustment granularity is an important factor in ensuring the effectiveness of network congestion control. In addition, this method cannot flexibly modify various traffic requirements, resulting in low adaptability. In view of this, the study aims to improve it from the perspective of intelligent learning. Equation (8) is the congestion window control.

$$w_{t+1} \leftarrow \mu_t w_t + \upsilon_t \tag{8}$$

In equation (8), μ_t and υ_t represent regulatory parameters. w_t refers to the congestion window width at moment t. Equation (9) is the average round-trip delay $I_{t,i}$ and the average sending window $R_{t,i}$.

$$\begin{cases} L_{t,i} = \alpha L_{t-1,i} + (1-\alpha)\left(ACK_{t,i} - ACK_{t-1,i}\right) \\ R_{t,i} = \dfrac{Cwnd_{t,i}}{\sum_{j=1}^{n} Cwnd_{t,j}} \end{cases} \tag{9}$$

In equation (9), $L_{t,i}$ refers to the packet loss rate of the i-th path. n refers to sub-streams number. Figure 7 shows the flow chart of congestion control-flow diagram based on Q-learning.

According to Figure 7, this congestion control method utilizes the environmental conditions obtained from network scenarios as the state of Q-learning. And according to the set strategy, the action with the maximum valueis selected to adjust the crowded window size, thereby controlling data transmission speed. As data transmission speed changes, the network environment also changes, and corresponding feedback is given to each individual to update the Q table. In this reciprocating cycle, an optimal relationship between window adjustment action and network conditions is ultimately obtained. In the exploratory state, traditional congestion control algorithms can provide stable network transmission and provide a good learning environment for the proposed algorithm. In the background, the proposed algorithm optimizes network congestion control by learning the mapping between network state and behavior to achieve more efficient bandwidth utilization and lower latency. This interaction can make network congestion control more intelligent and adaptive. This study introduces a dynamically transferable strategy in Figure 8.

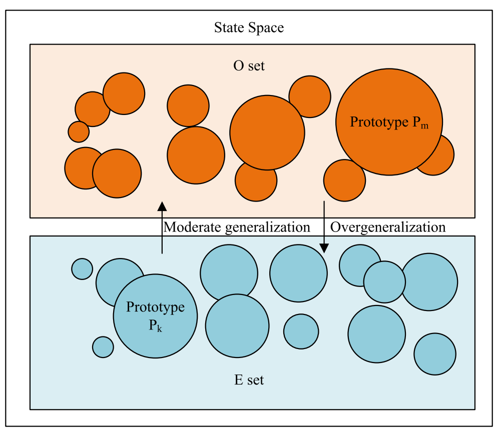


FIGURE 8. Prototype transfer process.

In Figure 8, in the initial state, the research first needs to construct a prototype set. This set can contain various types of prototypes, some of which may belong to O-class or moderately generalized sets, while others may belong to E-class or super generalized sets. When building this prototype set, it may be necessary to initialize all prototypes to complete. This may involve assigning an initial degree of generalization or weight to each prototype. Then, based on evaluating the performance of the prototype in simulation or practical applications,the degree of generalization for each prototype after every K time steps is calculated. When the prototype in O-class appears too special or not special enough, its generalization level needs to be adjusted to adapt to a wider range of E-class environments. Therefore, the prototypes in O-class that are far above or far below the average generalization level need to be transferred to the E-class region. When the prototype appears too ordinary or not special enough in E-class, it is necessary to adjust its generalization level to adapt to a more specific O-class environment. Therefore, the prototypes in theE-class region that are close to the average generalization level are transferred to the O-class region. The process of prototype transfer is dynamic and requires continuous adjustment and optimization. It needs to be adjusted and optimized based on the actual application effect and feedback to ensure its effectiveness and practicality. Through this method, on the one hand, it can ensure that a typical object will not invalidate its state value due to excessive access. On the other hand, it can also ensure that the object will not be mistakenly removed due to lack or little access for a certain period of time, so that the potential state value of the object will not be lost.

IV. UTILITY ANALYSIS OF ADAPTIVE TRANSMISSION CONTROL OPTIMIZATION MODEL FOR MULTI-BAND AND MULTI-NETWORK WIRELESS LINKS

To verify the resource optimization performance of the proposed adaptive encoding wireless network and the effectiveness of reinforcement learning-based congestion window regulation algorithm, a series of simulation experiments were conducted based on a given training dataset. The main performance evaluation indicators include encoding redundancy, throughput, and transmission time.

A. UTILITY ANALYSIS OF WIRELESS NETWORK DATA SCHEDULING MODEL BASED ON ANC

The structure of ANC based wireless routing network data scheduling model includes node, link, routing protocol cross-layer optimization, including 2500 nodes and 780kbps, which can form a complex network topology. To evaluate the performance of the multi-band and multi-network data scheduling model based on ANC, a Modeler product under the network simulation software Opnet was studied to achieve end-to-end multi-path transmission simulation experiments at the network model system level. The data used in the study includes a multi-band dataset, which contains network data on different frequency bands to simulate data transmission in a multi-band network environment. And multi-network datasets, which contain data from different types of networks, such as WiFi, 4G/5G, Bluetooth, etc. The simulation using Modeler can be roughly divided into six stages. They include configuring network topology, configuring business traffic, collecting relevant result statistics, debugging modules for re simulation, and ultimately publishing results and topology reports. Table 2 shows the multi-stream concurrent environment parameters.

TABLE 2. The multi-stream concurrent environment parameters.

Parameter	Numerical value	Parameter	Numerical value
Number of video blocks	46	Buffer Start Length	4
Video block length (s)	4	Number of links	2
Buffer capacity (s)	50	Buffer overflow waiting time	0.5
Group size range	≤25	Redundant size range within the group	≤5
Delay penalty factor	0.5	Re-buffering penalty factor	0.3
Buffer Penalty Factor	0.2	Lower limit of buffer length	15
Maximum buffer length	50	Packet size	1500

The link configuration includes path A and path B with corresponding communication methods of WIMAX and WLAN, core network latency of 50ms and 100ms, access bandwidth of 9 and 12Mbps, and access link latency of 25ms and 40ms, respectively. In the enhanced learning algorithm, samples will be classified based on three indicators: real-time bandwidth, packet loss rate, and backhaul delay. Figure 9 is a schematic diagram of the training dataset.

In Figure 9, during simulation, the setting of encoding group size is crucial. Setting it too much can cause significant decoding delay, while setting it too small cannot maximize the advantages of NC. Therefore, the range of packet size selected here is 0-30, and the range of redundant length is 0-10. In the parameters of A3C algorithm, the discount factor is set to 0.99, the network update step size is 0.01, the information content of video is 8, and the local proxies number is 16. When the byte is 30, according to IPv4 or IPv6 specifications, the IP header is constructed to encapsulate the short packet into the IP packet, and then the header cost and total length are calculated. If the data length plus the header cost exceeds the MTU, the data needs to be fragmented. If necessary, fill in with zeros to ensure that the data length is an integer of bytes. Figure 10 shows the decision results and encoding redundancy curve.

In the simulation, the size of data packet is set to 15, and the size of redundant data packet is set to 1. In order to achieve communication between different computers, it is necessary to encapsulate data into IP packets for transmission. When

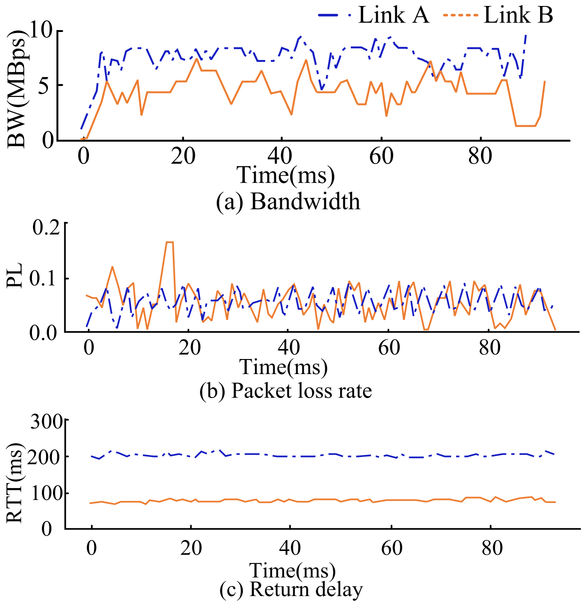


FIGURE 9. Schematic diagram of training dataset.

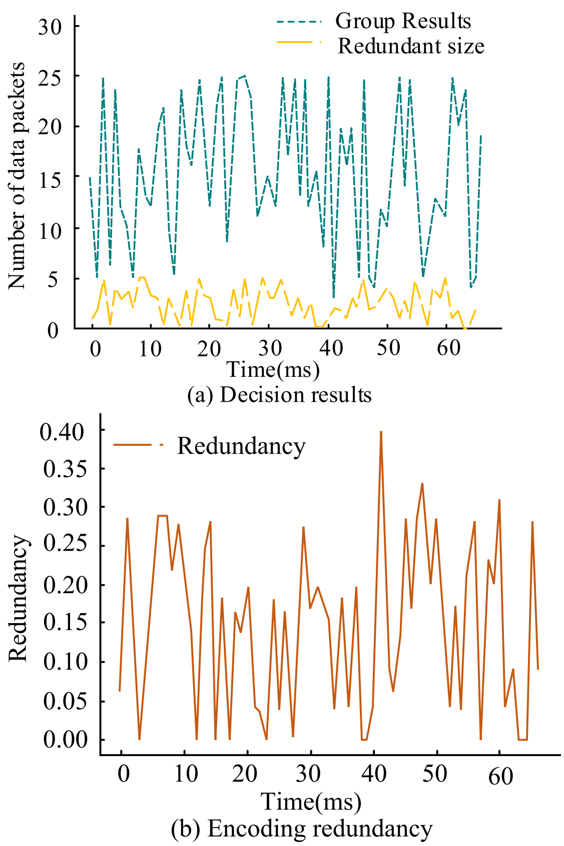


FIGURE 10. Decision results and coding redundancy curve.

encapsulating short data packets into IP packets, appropriate protocol stacks and encapsulation methods need to be used. Transport layer protocols such as UDP need to be studied to encapsulate data packets, and appropriate port numbers need to be used to identify different data flows. At time $t = 1$, due to the poor network conditions at this time, it is necessary to adjust the packet size and the size of redundant data packets within the packet. Among them, the value of group size is 13, while the size of redundant data packets within the group is 3. This algorithm can dynamically adjust the length of packets and redundant packets within packets according to network conditions during iteration, making it suitable for various network situations. These results confirm that in a few cases, the redundancy of the system is 0, which means that there is no need for NC. This method has an average redundancy of 14.5%. At $t = 41.8$, the encoding redundancy reached its maximum value, which means that the network condition is relatively poor at this time. So there will be more redundant encoded data packets to resist poor network environments. Figure 11 shows a comparison of throughput.

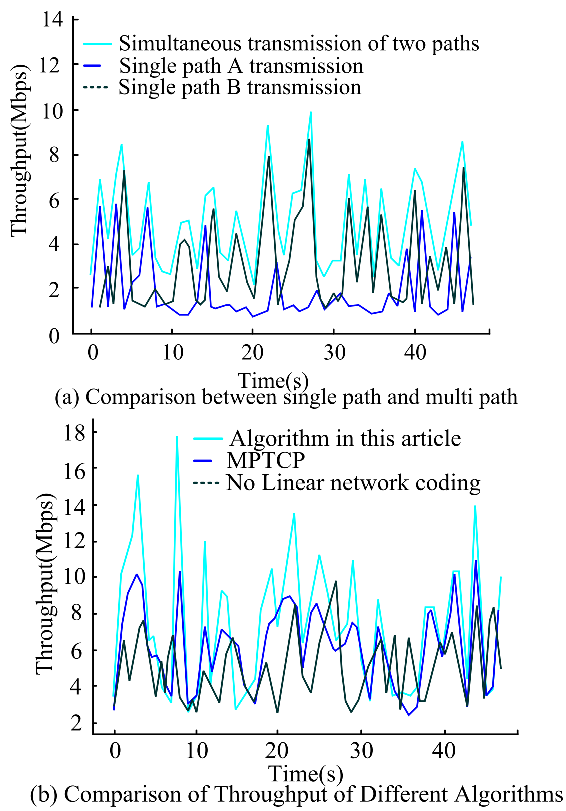


FIGURE 11. Throughput comparison chart.

Figure 11 compares the throughput of multi-path and single-path transmission, showing that multi-path transmission can achieve higher throughput. Compared with encoding methods that do not require a network, adaptive NC methods have higher throughput. On this basis, an adaptive algorithm based on this algorithm is proposed. However, when NC algorithm is not used, the confusion at the receiving end can cause queue head congestion, resulting in slower transmission speed for the sender and an un-reasonable decrease in throughput. TheANC scheme introduced has significantly improved throughput compared to the pipeline NC scheme, with an increase of about 30%-40%. Although the trends of these two methods are consistent, the former can quickly respond to changes in the network. Figure 12 shows the curve of the number of data packets with transmission time and the comparison of receiver cache time.

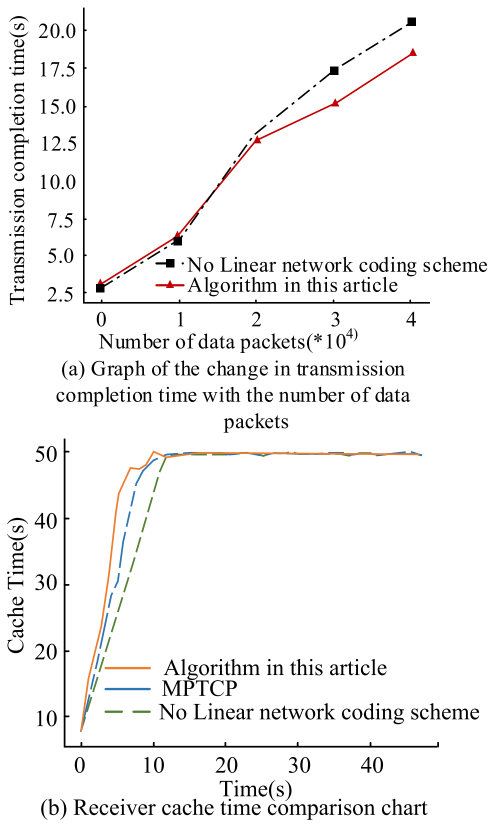


FIGURE 12. Curve of the number of data packets changing with transmission time and comparison of receiver cache time.

From Figure 12, the time required to achieve image transmission using adaptive NC method decreases with the increase of transmitted data packets. When there are fewer data packets, not using NC scheme requires less transmission time because there is a certain delay in encoding. Compared with unused NC methods, using adaptive NC methods can obtain larger buffer space faster and takes less than 8 seconds. The pipeline NC is higher than 10s.

B. ANALYSIS OF CONGESTION CONTROL ALGORITHM PERFORMANCE RESULTS

This research selected NewReno, CUBIC, Compound, Bottleneck Bandwidth and Round trip Time (BBR) algorithms, and Decision Fuzzy Algorithm as the performance comparison algorithms based on Q-learning proposed in the research. TheNewReno algorithm is an end-to-end congestion control algorithm based on window feedback mechanism, where the sender determines how to adjust the size of the congestion window based on the information carried by the received feedback packet. This algorithm is an improvement of the fast recovery algorithm, taking into account the loss of multiple packets within a single sending window. The CUBIC algorithm is the default congestion control algorithm on current Linux systems. Its congestion control window growth function is a cubic function, designed to have better scalability in the current fast and long-distance network environment. The congestion window growth of CUBIC is independent of the round-trip time between customers and servers, thus better ensuring fairness between flows. The BBR algorithm represents the exact model of the network path through which the transmission flow passes. It does not require packet loss to measure whether congestion occurs, but directly models the network to avoid and respond to real congestion. The design concept of the Compound algorithm is to combine the advantages of delay-based algorithms and packet loss-based algorithms, which fully utilizes high-speed network bandwidth, while maintaining fairness with traditional TCP Reno algorithms. In the experiment, the sender is a single point transmission, with a bottleneck link bandwidth of 5.0Mb, a bottleneck link latency of 10.0ms, and a queue length of 100pkt. Figure 13 shows the comparison results of average throughput and latency for different congestion control algorithms.

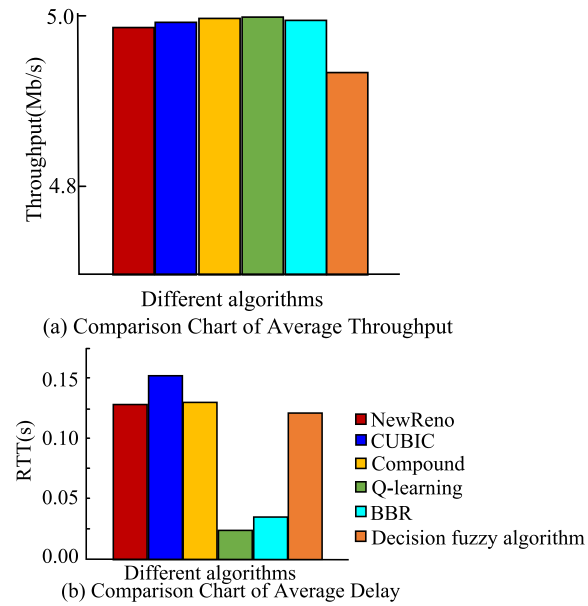


FIGURE 13. Comparison of throughput results of different congestion control algorithms.

From Figure 13, the proposed algorithm performs well in basic congestion control. And like other control algorithms, this algorithm maintains a bandwidth utilization rate of nearly 99%, and can maintain a higher transmission rate and lower transmission delay while maintaining a higher transmission rate. However, the congestion control algorithm based on decision fuzzy has not been widely promoted and its convergence is not good enough. This has led to its unsatisfactory performance in practical applications, resulting in a lower average bandwidth utilization rate compared to the algorithms proposed in the study. In practical applications, its average delay is about 0.1 seconds higher than the algorithm proposed by the research institute. Figure 14 shows the

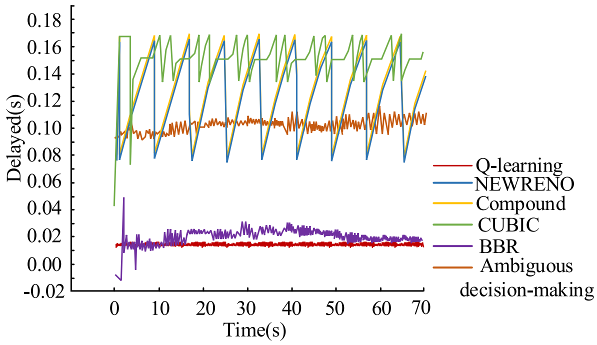


FIGURE 14. Comparison chart of real time delay of various congestion control algorithms.

real-time delay comparison of various congestion control algorithms.

From Figure 14, the real-time delay curve of the proposed algorithm has a smaller fluctuation amplitude compared to other algorithms, and the overall fluctuation value varies around 0.015s, with ups and downs not exceeding 0.005s. The CUBIC algorithm not only has a high delay value, but also exhibits significant fluctuations. Its real-time delay range is between 0.01s and 0.17s, which is one order of magnitude higher than the algorithm proposed in the study. Although the NewReno algorithm has a delay only higher than the algorithm proposed in the study, its fluctuations are more frequent, making it more unstable. Figure 15 shows the comparison of real-time throughput curves of various congestion control algorithms.

According to Figure 15, intheNewReno algorithm, the throughput difference between each stream is constantly changing, and there is no balanced convergence, which is the worst. Inthe CUBIC algorithm, the throughput of the four links gradually reaches a stable state, but the throughput of each link varies greatly and does not have fairness. In decision fuzzy algorithms, the throughput rates of each data stream tend to be consistent, but there are still significant differences in the throughput rates of the four data streams. The proposed method gradually increases the throughput of each data stream. And the proportion of throughput in each data stream tends to approach and eventually converges, with good fairness. Figure 16 shows the throughput comparison results of various congestion control algorithms in a packet loss resistant environment.

When network packet loss occurs, traditional loss-based congestion control methods such as NewReno and CUBIC will significantly reduce the system's throughput. When the network packet loss rate approaches 8%, its utilization of bandwidth is only 21%. The method proposed by the research institute only reduces the throughput performance of the system after the packet loss rate reaches 12%, which to some extent delays the negative effects brought by the increase in packet loss rate. The reason why the throughput performance of the algorithm proposed by the research decreases after the packet loss rate reaches 12% is that the throughput represents the current communication traffic value, and the size depends

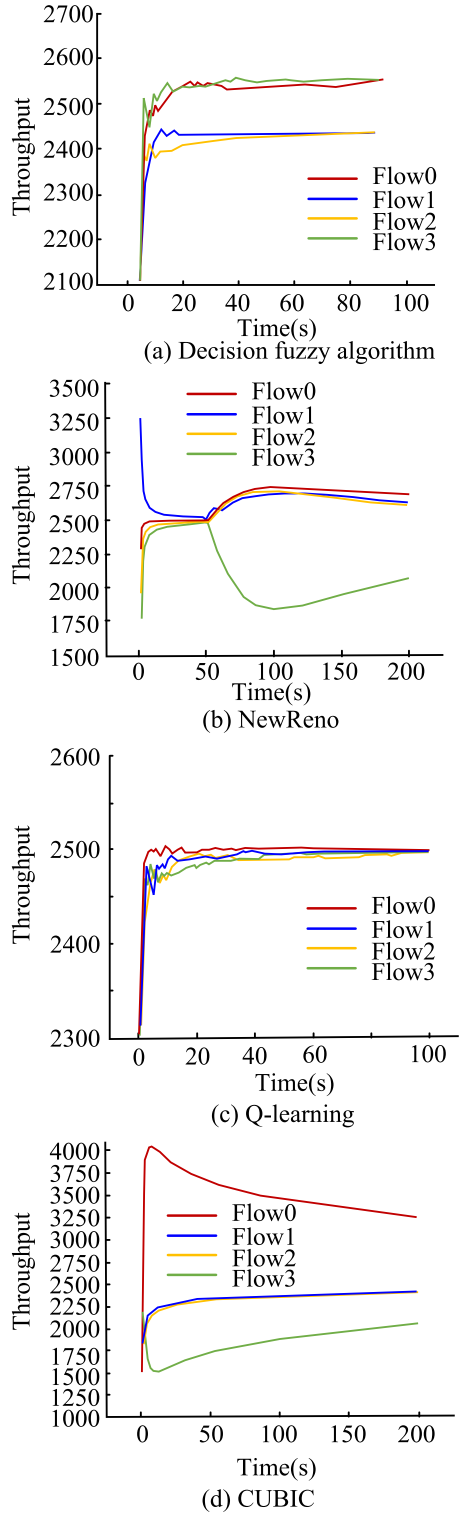


FIGURE 15. Comparison of real-time throughput curves of various congestion control algorithms.

on the current network packet size and the current number of packets. The packet loss rate represents the ratio of the number of lost data packets to the sent data group. Therefore, for any network, increasing the packet loss rate to a certain value will lead to a decrease in throughput performance.

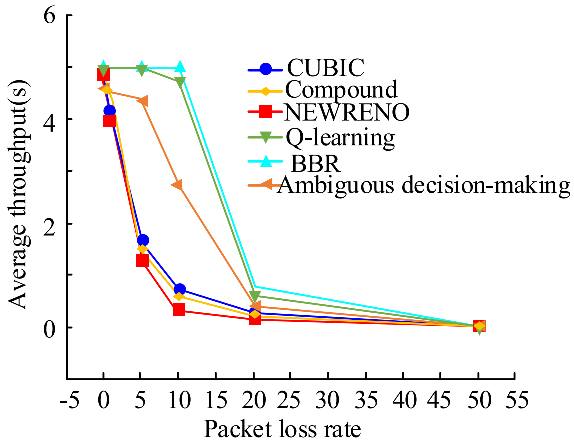


FIGURE 16. **Throughput comparison results of various congestion control algorithms in packet loss resistant environments.**

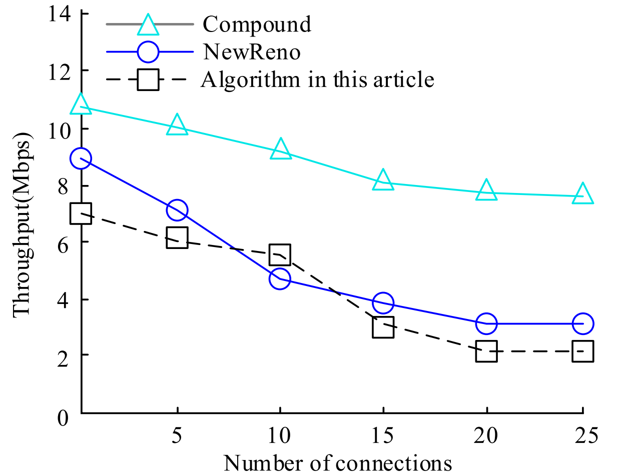


FIGURE 17. **Throughput of different congestion control algorithms when the number of connections increases.**

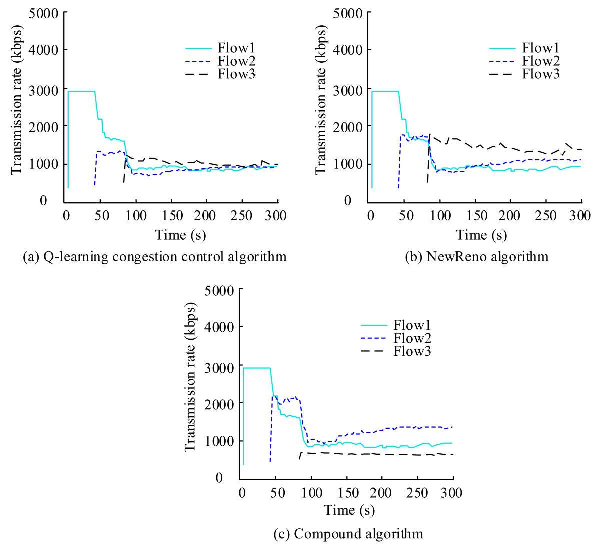


FIGURE 18. **Network fairness of different congestion control algorithms.**

The network throughput based on decision fuzzy algorithm gradually decreases with the increase of packet loss rate. Although the throughput rate is slower than other networks such as CUBIC, overall it is still in a very low state. Compared with the NewReno and Compound algorithms, the proposed algorithm still has higher throughput under the same loss rate [29], [30].

From Figure 17, as the number of connections, i.e. the number of multiple frequency bands, increases, the proposed congestion control algorithm has a smaller decrease compared to the NewReno and composite algorithms. This means that when facing more network connections or more complex network environments, the algorithm proposed by the research can better maintain its throughput without significantly reducing it like NewReno and composite algorithms. Generally, it can maintain a relatively high throughput range between 7.8 and 10.9 Mbps, indicating that the algorithm has high efficiency and performance in network congestion control. The throughput of NewReno algorithm and composite algorithm is generally between 2 and 9.5 Mbps, which is relatively low, indicating that these two algorithms may not perform as well as the algorithms proposed in the study when facing more network connections or more complex network environments.

From Figure 18, the transmission rates of the three data streams of the Q-learning-based congestion control algorithm proposed by the research converge to 1Mbps, and the convergence process is relatively stable with little fluctuation. However, the three data streams of the NewReno algorithm and the Round algorithm cannot converge to a unified transmission rate, with a difference of around 0.3Mbps. This indicates that the congestion control algorithm proposed by the research can achieve equal competition among multiple data streams and better fairness within the protocol. The real-time throughput curve can reflect the performance of different congestion control algorithms under different network conditions. The fairness of congestion control algorithms is reflected in their resource allocation for different flows. If an algorithm can allocate resources reasonably based on the priority or demand of different flows, it has high network fairness. Obviously, from Figures 15 and 18, the congestion control algorithm proposed by the research is applicable to multiple data streams.

From Figure 19, when the transmission rate varies between 500 and 2500, the CPU utilization of the congestion control algorithm proposed by the research is all below 0.1, with a maximum of 0.06. The CPU usage of NewReno and Compound algorithms shows a significant increase as the transmission rate increases exponentially, with values ranging from 0.2 to 0.9. Therefore, this indicates that the control algorithm proposed in the study has more advantages in terms of friendliness in network resource utilization.

V. DISCUSSION

In the research of multi-path transmission, there are two important research issues: one is the packet scheduling problem, and the other is the congestion control of multi-path transmission. Due to the varying quality of multi-bands in wireless networks, to fully utilize multiple paths for data

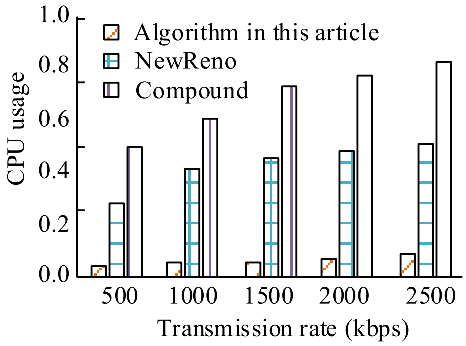


FIGURE 19. Central processing unit occupancy rate of different congestion control algorithms.

transmission, it is necessary to obtain the state information of each link and schedule data packets based on it. By using reasonable packet scheduling algorithms at the sending end, data packets arrive at the receiving end in order. Most references are studying packet scheduling algorithms and designing reasonable packet scheduling algorithms to maximize the required targets for transmission. For the scenario of concurrent transmission in wireless networks, the research first proposes a wireless link concurrent transmission control framework based on adaptive NC, and then introduces the functions of each module separately. A3C reinforcement learning is utilizedto obtain the optimal encoding strategy, and then the encoded data packets according to the proposed path quality-based packet distribution algorithm are scheduled. The simulation results show that compared to not using NC schemes or pipeline NC schemes, the proposed scheme can achieve higher transmission rates and make the video fill the buffer more quickly, greatly improving the user experience.

And the design process of traditional congestion control algorithms is very complex and usually requires rule design based on specific network conditions, resulting in poor universality. Its performance also falls into bottlenecks or other defects with the development of computer network technology. For example, TCP Vegas performs very unstable in fairness, which means it is easily affected by fluctuations in the network environment and cannot maintain a relatively stable state for a long time. The TCP Cubic algorithm is the opposite situation, as its excellent competitiveness makes it difficult for other algorithms to coexist with TCP Cubic streams on the same link. The congestion control algorithm proposed by the research can use reinforcement learning technology to automatically learn autonomously in different network scenarios, thereby improving the research and development speed and performance of congestion control algorithms in emerging network environments.

VI. CONCLUSION

Due to differences in the quality of multi-bands, the situation of network and terminal mobility is complex and variable, and the multi-path traffic will inevitably lead to header congestion, buffer congestion, and so on. In response to these issues, the transmission control and congestion control of multi-path parallel transmission in wireless systems are studied. A transmission control algorithm based on ANC is proposed to address the problem of packet disorder in multi-path concurrent transmission, which combines reinforcement learning with NC. A learning-based control algorithm is proposed for congestion control problems. These results confirm that the proposed ANC-based data scheduling algorithm has significantly improved throughput compared to the pipeline NC scheme, with an increase of over 30%. When faced with a large number of data packets, the proposed algorithm reduces latency by about 25% compared to the pipeline NC method. The proposed congestion control algorithm has the smallest fluctuation amplitude in the delay curve, with a fluctuation level value of 0.015s. It indicates that this algorithm also ensures fairness among multiple data streams when sharing bottleneck links, achieving lower computational overhead. The innovation of this study lies in proposing a multi-band and multi-network data scheduling model based on ANC. This method combines reinforcement learning with NC. The encoded network can break free from the tight binding relationship between data transmission and sequence numbers, effectively solving the problem of chaos. The disadvantage of this study is that it did not consider the correlation between video packets, resulting in higher encoding costs. In the future, it will be possible to combine NC with video encoding to improve encoding efficiency.

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